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厦门大学

硕士学位论文

基于适应性分整广义自回归条件异方差模型的预期损失分析

Expected Shortfall based on Adaptive FIGARCH model

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摘 要

在风险管理领域，在险价值（VAR）是最常见的风险度量方法之一。在险价值（VAR）指的是在一定时期内，对一个固定概率而言的预期最大损失值。与常见的在险价值（VAR）方法相比，期望损失法（ES）和有条件的在险价值法（CVAR）更常被采用，这是因为它们估计了超过在险价值时的预期损失。本文介绍了基于适应性 FIGARCH 模型的期望损失，该模型比 FIGARCH 模型更能准确的估计波动率。

在后验测试中，我们采用了国际市场数据，对其进行 Kupiec 检验和百分之九十五和百分之九十九置信区间下的动态分位数回归检验。

本文进一步显示了基于适应性 FIGARCH 模型和基本 FIGARCH 模型估计的不同预期损失结果。

关键词： 预期损失；适应性 FIGARCH 模型；长记忆；风险管理

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Abstract

In risk management, the most common type of measurement is Value-at-Risk (VaR). This is the amount of risk over a period of time with a fixed probability. In comparison to the common VaR, Expected Shortfall (ES) or Conditional Vaue-at-Risk (CVaR) is more popular to use because it predicts the amount of loss as it exceeds VaR value. This paper shows the Expected Shortfall from the Adaptive-FIGARCH model, the model that mathematically improves from the basic FIGARCH model for a more accurate forecasting volatility.

For performing backtesting, we provide a popular method called the Kupiec test and Dynamic Quantile test on 95% confident level and 99% confidence level using international market data under the t-distribution.

The results show that both models are valid. However, Adaptive-FIGARCH is not as effective as the basic FIGARCH model.

Key Words: Expected Shortfall; Adaptive FIGARCH model; long memory; risk Management

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Chapter 1 Introduction

1.1 Motivation and Background

Risk measurement was first introduced in 1970 after a sudden increase in financial instability.

Many economists consider the financial crisis of 2007–2008, also known as the Global Financial Crisis, the worst financial crisis since the Great Depression of the 1930s. It resulted in the threat of total collapse of large financial institutions, the bailout of banks by national governments, and a period of downturns in stock markets around the world known as the Great Recession. In many areas, the housing market also suffered, resulting in evictions, foreclosures and prolonged unemployment. The crisis played a significant role in the failure of key businesses, declined in consumer wealth estimated in trillions of U.S. dollars, and a downturn in economic activity leading to the 2008–2012 global recession and contributing to the European sovereign-debt crisis. The active phase of the crisis, which manifested as a liquidity crisis, can be dated from August 9, 2007, when BNP Paribas terminated withdrawals from three hedge funds citing "a complete evaporation of liquidity".

From all the instability around the world, financial institutions needed to manage risk using various types of methods. One of most popular methods was the Value at Risk (VaR).

The VaR method can be used by financial institutions to calculate capital charges in respect of their financial risk. However, even if VaR is said to be useful for financial institutions to understand risk, it is believed that VaR is not the best measure. Expect Shortfall (ES) is more attractive coherent risk measure and has been used by many professionals. We estimate ES by Adaptive FIGARCH, FIGARCH, HYGARCH model under t-distribution.

In addition, based on Basel Committee on Banking Supervision (BCBS) has proposed an adoption of Expected Shortfall instead of VaR as the new quantitative risk metrics system. (Basel Committee Proposes Using Expected Shortfall Instead of

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VaR in Market Risk Management, 2012)

The reasons behind this are there is an increases in objective boundaries between trading book and banking book. Also, it is said to be better at capturing “tail-risk”. Two of the policies agreed by BCBS members are to reduce risk in the internal model approach and to standardize approach that is considered to be more risky, thus using the Expected Shortfall would reduce it. (Basel Committee Proposes Using Expected Shortfall Instead of VaR in Market Risk Management, 2012)

This made a huge impact on the author’s motive to conduct a research on finding the Expected Shortfall using the models the author has chosen. The author expects that Adaptive FIGARCH model, which is a long memory and structural break, would be able to find an efficient value of Expected Shortfall.

1.2 Literature Review

Delbaen (2002) and Artzner et al. (1997) introduced the Expected Shortfall risk measure, the most attractive risk measure, which equals the expected value of the loss given that a VaR violation occurred. Many authors have studied Expected Shortfall risk. Yamai & Yoshiba (2004) have compared the two measures, VaR and ES, for which they argued that VaR is not reliable during market turmoil, while ES could be a better choice overall.

The FIGARCH model was proposed by Baillie (1996) for developing a more flexible class of processes for conditional variances that are more capable of explaining and representing the observation of temporal dependencies in financial market volatility.

Research from Lobato & Savin (1998), Beine & Laurent (2000), Morana & Beltratti (2004) and Martens et al. (2004) have an idea that volatility of financial returns should include long memory and structural changes. Moreover, Mikosch & Starica (1998) and Granger & Hyung (2004) have simulated evidence that long memory can be detected from a time series with breaks. Furthermore, Starica & Granger (2004) found that in a non-stationary model, by allowing for breaks the

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unconditional variance, will lead to a better performance than long memory model in forecast, but not in a short horizon, Diebold & Inoue (2001) show that Markov switching process can generate long memory in a conditional mean. All of these researches support various reasons for an improvement in Adaptive FIGARCH model.

The Adaptive FIGARCH model, introduced by Baillie (2009), is used for proposing both structural and long memory volatility processes developed from the original FIGARCH model by employing flexible function form from Gallant (1984). The advantage of Adaptive FIGARH model is its accuracy in forecasting volatility.

From Hansen (1994) and Lumsdaine (1996) show that QMLE is strictly stationary and mathematically ergodic.

Kupiec (1995) used an unconditional coverage backtesting processes. In addition to that, DQ Test, proposed by Engle & Manganelli (2004), is a linear regression backtesting model, was introduced.

1.3 Overview of this Thesis

Baillie (2009) explained that the Adaptive FIGARCH model can forecast more accurately than the basic FIGARCH model but it does not mean Adaptive FIGARCH model can estimate an efficient Expected Shortfall. The purpose of this paper is to introduce ES estimation by Adaptive FIGARCH model and compare it with the FIGARCH model; this will give us a more comprehensive understanding about the efficiency of the Adaptive FIGARCH model.

The first estimation is model estimation, each parameter estimated values are from the MLE method. The second estimation is the backtesting estimation and Expected Shortfall estimation.

International stock index, both Asian Stock data index and U.S. Stock data index is used as the data. The data is a 10-year period, which inevitably includes the period of financial crisis. Thus, it is good for Expected Shortfall estimation.

A backtesting method is used to test the efficiency of the VaR estimation but we can also use it to explain the efficiency of Expected Shortfall. The Kupiec test is the

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most common popular backtesting method for VaR and Expected Shortfall, and the Quantile test explains the VaR estimation by the regression method.

1.4 Structure of the Paper

Introduction

Introduction describes the motivation for the research, consisting of literature review and overview of this paper.

Theoretical Background

The chapter mathematically describes the theoretical background of the paper. We first describe the theory of long memory model, which comprises of FIGARCH, A-FIGARCH, and HYGARCH model. Then later in this chapter, it describes the data properties, which are financial return and distribution.

Next to that is risk management theory, which describes about Value at Risk and Expected Shortfall, the backtesting and model estimation method.

Data and Methodology

This chapter describes the data set the author uses in the estimation and during the process of estimation.

Empirical Result

The chapter begins with the descriptive statistics of all data set. Then the author shows the model estimation. Finally the author shows the estimated values obtaining from backtesting and the Expected Shortfall values.

Conclusion

The final chapter concludes all study of this thesis paper.

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Chapter 2 Theoretical Background

In this part, we will see the theoretical background behind each model, which, of course, includes mathematical explanation of the models.

2.1 Long Memory Volatility Model

2.1.1 FIGARCH Model

Fractionally Integrated Generalized Auto Regressive Conditionally Heteroskedastic (FIGARCH) Model was introduced by Baillie et al. (1996) and Baillie & Morana (2009), which was an extension from GARCH family model. The conditional variance of the model implies a slow hyperbolic rate of decay for the influence of lagged squared innovation. FIGARCH model with constant mean can be written as:

$$y_t = ? + \varepsilon_t \tag{2.1}$$

$$\varepsilon_t = z_t \sigma_t \text{, where } z_t \sim N(0,1) iid \tag{2.2}$$

$$(1-\beta L)\sigma_t^2 = \omega_0 + [1-\beta L-(1-\varnothing L)(1-L)^d]\varepsilon_t^2 \tag{2.3}$$

Parameter d is the fractional differencing parameter. For $0 < d < 1$, unconditional variance of a FIGARCH model is not defined well, however, the FIGARCH model is strictly stationary and ergodic for $0 < d < 1$. (Baillie 1996). The model is estimated by maximizing the Gaussian log likelihood function.

How GARCH model becomes FIGARCH model, we begin our mathematical derivation with GARCH (p,q) model:

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \tag{2.4}$$

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where L denotes the backshift operator, implying

$$\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \ldots + \alpha_q L^q \tag{2.5}$$

$$\beta(L) = \beta_1 L + \beta_2 L^2 + \ldots + \beta_p L^p \tag{2.6}$$

From equation (4), (5) and (6), we can rewrite them as

$$\sigma_t^2 = \omega\left[1-\beta(L)\right]^{-1} + \alpha(L)\left[1-\beta(L)\right]^{-1}\varepsilon_1^2 \tag{2.7}$$

$$\left[1-\alpha(L)-\beta(L)\right]\varepsilon_t^2 = \omega + \left[1-\beta(L)\right]v_t \text{ , given } v_t = \varepsilon_t^2 - \sigma_t^2 \tag{2.8}$$

When we consider the following:

$$\varnothing(L) = \left[1-\alpha(L)-\beta(L)\right](1-L)^{-1} \tag{2.9}$$

$$(1-L)^d = \sum_{k=0,\infty}\Gamma(k-d)\Gamma(k-d)^{-1}\Gamma(-d)L^k \text{ , } \Gamma(\cdot) \text{ is the Gamma function} \tag{2.10}$$

The formula becomes

$$\varnothing(L)(1-L)\varepsilon_t^2 = \omega + \left[1-\beta(L)\right]v_t \tag{2.11}$$

As we substitute $(1-L)$ with $(1-L)^d$ where d is fractional differencing parameter with the range of $0 < d < 1$, we get

$$\varnothing(L)(1-L)^d\varepsilon_t^2 = \omega + \left[1-\beta(L)\right]v_t \tag{2.12}$$

Therefore, we get FIGARCH (p,d,q) equation:

$$(1-\beta L)\sigma_t^2 = \omega_0 + [1-\beta L-(1-\varnothing L)(1-L)^d]\varepsilon_t^2 \tag{2.13}$$

We have a stationary long memory process when $0 < d < 1$. However, when $d = 1$, the process has a unit root which, of course, leads to a permanent shock effect This is

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the same as IGARCH model. If $d = 0$, the process becomes an ordinary GARCH model without long memory property (Baillie, 1996).

2.1.2 Adaptive FIGARCH model

For the new improvement in the original model, Baille (2009) proposed a new model from basic FIGARCH model, which is called the Adaptive FIGARCH (A-FIGARCH) model. The model is said to be better than the original because the original model has drawbacks. The original model assumes that there is one regime of the conditional volatility over the entire period. Therefore, this newly improved model overcomes such drawback. The model shares both of the properties of structure break and long memory volatility model by employing flexible function form of Gallant (1984), Baille (2009) shows that A-FIGARCH model has better performance relatively to basic the FIGARCH model.

The volatility process is represented by the A-FIGARCH model *(p,d,q,k)* with trigonometric terms *(k).* A-FIGARCH model has the same equations for finding a mean and error, which are equations (2.1) and (2.2), and the model formula is:

$$(1-\beta L)\sigma_t^2 = \omega_t + [1-\beta L-(1-\varnothing L)(1-L)^d]\varepsilon_t^2 \qquad (2.14)$$

ω_t is a time vary function

$$\omega_t = \omega_0 + \sum_{j=0}^{k}\left[\gamma_j \sin\left(\frac{2\pi jt}{T}\right) + \delta_j \cos\left(\frac{2\pi jt}{T}\right)\right] \qquad (2.15)$$

The estimating function of Adaptive FIGARCH model is QMLE, same as the FIGARCH model. Adaptive FIGARACH model is indeed valid and parsimonious at k=1 and k=2.

2.1.3 HYGARCH model

HYGARCH (Hyperbolic GARCH) was introduced by Davidson (2004), the model generalizes the FIGARCH model.

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HYGARCH has the same equations for finding a mean and error, which are equations (2.1) and (2.2), and the model formula is:

$$(1-\beta L)\sigma_t^2 = \omega_0 + [1-\beta L-(1-\varnothing L)(1+\alpha((1-L)^d-1))]\varepsilon_t^2 \quad (2.16)$$

HYGARCH process is stationary when $\alpha < 1$ (or $\log(\alpha) < 0$), and when $\alpha > 1$ this process is not stationary, the HYGARCH model is same as the FIGARCH model when $\alpha = 1$. In the estimating process, the parameter is $\log(\alpha)$, not α. Estimation function of HYGARCH model is QMLE, same as FIGARCH model.

For all long memory models, auto correlation function (ACF) of model follows by this equation

$$ACF = \frac{d\Gamma(k-d)}{\Gamma(1+k)\Gamma(1-d)} = O(k^{-1(-d)}) \quad (2.17)$$

$$\therefore Cov\left(y_{t-k}^2, y_t^2\right) = O\left(k^{-1(-d)}\right) \quad (2.18)$$

where d is the value between 0 and 1, the less value of d is, the more implying that it is a long memory of volatility.

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2.2 Data Properties

2.2.1 Financial Return

Our data is the rate of return in the form of geometric return. P_t denotes financial asset price at time *t*. The return in percentage can be derived as:

$$r_t = 100 \times \left(lnP_t - lnP_{t-1} \right) \tag{2.19}$$

The benefit to using geometric return is that when we need to do juxtaposition between two stocks, we look at the percentage of the profit return. Moreover, geometric return is more accurate than arithmetic return.

2.2.2 Data Distribution

Return data is more frequently a small return, it seems to be leptokurtic, which is excess kurtosis and has more mass in the tail area of the distribution graph. We prefer to use t-distribution for return data because it is distributed for leptokurtic type of data.

The t-distribution is similar to normal distribution. However, this distribution has heavy tails in the distribution graph and is controlled by the shaped parameter. A small shaped parameter gives heavy tails in the distribution graph.

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